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Diagnosing Voltage and Current Imbalance of Three-Phase Induction Motor with Artificial Neural Network Method

Diagnosa Ketidakseimbangan Tegangan dan Arus Motor Induksi Tiga Fasa dengan Metode Artificial Neural Network

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Abstract

Industries today are increasingly using three-phase induction motors. It is an important tool for production continuity and progress. Power quality issues, such as voltage and current imbalance, are prevalent today and can lead to motor overheating and inefficiency. Even worse, interruptions can impede the production process, resulting in losses and higher repair costs. This study uses MATLAB and microcontroller-based Artificial Neural Network (ANN) methods to identify voltage and current imbalances in three-phase induction motors, thereby preventing significant damage and preserving the service life. ANN works by learning and classifying the collected data. The testing flow uses 30% of the data, while the training flow uses the remaining 70%. The classification results showed that 60.49% of the voltages were balanced, and 31.59% were unbalanced. We found an accuracy percentage of 99.51% for both balanced and unbalanced voltages, a mean squared error (MSE) of 0.0167, and a root mean squared error (RMSE) of 0.1294.

Keywords: diagnosis of imbalance, three phase induction motor, artificial neural network, arduino UNO.

***SDGs*:**

Abstrak

Motor induksi tiga fasa semakin digunakan oleh industri saat ini. Ini adalah alat yang sangat penting untuk keberlangsungan produksi dan kemajuannya. Masalah kualitas daya seperti ketidakseimbangan tegangan dan arus adalah salah satu masalah yang dapat terjadi dan umum saat ini, yang dapat menyebabkan motor panas dan tidak efisien. Lebih buruk lagi, gangguan dapat menghambat proses produksi dan menyebabkan kerugian dan biaya lebih tinggi untuk memperbaikinya. Untuk mencegah kerusakan yang signifikan, dan bahkan mempertahakan masa pakai, metode Artificial Neural Network (ANN) berbasis MATLAB dan mikrokontroler digunakan dalam penelitian ini untuk mengidentifikasi ketidakseimbangan tegangan dan arus di motor induksi tiga fasa. ANN bekerja dengan mempelajari dan mengklasifikasikan data yang terkumpul. 30% dari data tersebut digunakan untuk alur pengujian, dan 70% lainnya digunakan untuk alur pelatihan. Perolehan klasifikasi menunjukkan bahwa 60,49% tegangan seimbang dan 31,59% tegangan tidak seimbang. Untuk tegangan seimbang dan tidak seimbang, ditemukan persentase akurasi 99,51%, dan *Mean Squared Error* (MSE) sebesar 0,0167, dan *Root Mean Squared Error* (RMSE) sebesar 0,1294.

Kata Kunci: diagnosa ketidakseimbangan, motor induksi tiga fasa, *artificial neural network*, arduino UNO.

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1. INTRODUCTION

Today, the industry is increasingly using three-phase induction motors (MI) as a crucial tool for production continuity and progress. According to researchers Chauhan & Singh and Laadjal et al. (Chauhan and Singh, 2019; Laadjal *et al.*, 2021), more than 80% of electric motors used in industry and factories are three-phase induction motors.

Equipment interruptions, small stops, and sudden stops are the industry's leading causes of production problems. Researchers Jiang et al., report that sudden interruptions in industrial equipment account for nearly 79.6% of production problems in industry (Jiang *et al.*, 2022). Voltage imbalance in three-phase induction motors is a common problem today. Unbalanced voltage is a voltage value that does not match the three-phase voltage system of an electrical distribution system. Voltage imbalance can cause the current of a three-phase induction motor to become unbalanced, increase several times, and cause this motor to become hot and decrease efficiency.

Given the various problems mentioned above, it is necessary to conduct research that can diagnose voltage and current imbalances in three-phase induction motors. This will allow for continuous monitoring, the prediction of disturbances or degradation, and the implementation of preventative measures to prevent unwanted disturbances in these motors. Predictive maintenance activities incorporate these diagnostic actions. According to Namuduri et al., this predictive maintenance works by detecting unusual system behavior and providing an early warning for catastrophic system damage (Namuduri *et al.*, 2020). Therefore, diagnosing voltage and current imbalances in three-phase induction motors can provide real benefits to the industry.

Researchers have conducted numerous studies on diagnosing failures or damage in three-phase induction motors, striving to find the most effective method that not only ensures the desired quality and safety of these motors, but also streamlines the process and reduces the need for costly repairs. Researchers in the field of induction motors, such as Laadjal et al. and Fortes et al., have expressed their belief that voltage and current imbalances significantly impact three-phase induction motors (Fortes *et al.*, 2018; Laadjal *et al.*, 2021). These imbalances not only reduce the efficiency of induction motors but can also lead to a series of heating issues. These issues can cause further losses, vibration, acoustic noise, and torque loss, ultimately reducing the service life of induction motors, then Zhang, et al., conducted research on voltage imbalance and distortion in three-phase induction motors (Zhang, An and Wu, 2018). Researchers say that if the terminal voltage is uneven and distorted, it has a big effect on the efficiency of induction motors and makes the loss characteristics of induction motors more complicated. It is therefore critical to take action to reduce motor losses and increase motor efficiency.

Researchers worldwide are seeking solutions to address the numerous interference issues in three-phase induction motors to prevent significant losses due to fatal damage to MI. One of them, Chouhan et al., conducted research on fault diagnosis in induction motors operating under the same conditions for various speeds and loads with an artificial neural network (ANN) (Chouhan *et al.*, 2020). Based on the research results, we can conclude that this study is effective, independent of the motor's speed or load, and applicable to any operating condition. For the same speed and load conditions, the research results are approximately 96% accurate. The researchers also propose a deep learning method and compare its results with those of an artificial neural network (ANN). Researchers Chouidira et al., Mekhalfia et al., Dhomad & Jaber, and Jorkesh & Poshtan, carried out nearly identical research on failure diagnosis in three-phase induction motors using ANN methods (Chouidira, Khodja and Chakroune, 2019; Mekhalfia, Khodja and Chakroune, 2019; Dhomad and Jaber, 2020; Jorkesh and Poshtan, 2021). The researchers performed failure diagnosis using data from induction motors, then divided the data into 70% train data and 30% test data. They also proved that the ANN can effectively diagnose induction motor failures. Dhomad and Jaber, research further confirms this, demonstrating that by analyzing current motor data using these methods, we can also diagnose the physical condition of the motor's bearings (Dhomad and Jaber, 2020). But it's not the same as the work that Priyandoko et al., did on using ANN and discrete wavelet transform (DWT) to predict bearing defects that will happen in three-phase induction motors (Priyandoko *et al.*, 2020). In that study, using both ANN and DWT to predict bearing defects in three-phase induction motors was successful with an accuracy of 98.9%, so using both together could be a new way to research other systems to get close to 100% accuracy.

Three groups of researchers Okelola & Olabode, Boimau et al., and Irawan et al., used ANN research along with MATLAB simulation and Mean Squared Error (MSE) calculation to figure out why three-phase induction motors fail (Okelola and Olabode, 2018; Boimau *et al.*, 2020; Irawan *et al.*, 2020). The research demonstrates that MSE can diagnose the failure conditions of three-phase induction motors with good, simple, reliable, and efficient predictions, reaching 95% accuracy when the error rate is less than 5%. In contrast to research from Boum et al., they conducted research on fault diagnosis in three-phase induction motors using fuzzy logic, artificial neural networks, and hybrid systems. Researchers proved that fuzzy logic can detect faults expressed at 95% accuracy, while ANN and hybrid systems (a combination of fuzzy logic and ANN) can detect faults at 100% accuracy (Boum *et al.*, 2018). The training process determines their accuracy. In addition, combining these two methods is more advantageous than just one method alone.

Considering the findings from the literature review, particularly the research by Okelola and Olabode (Okelola and Olabode, 2018), the author plans to incorporate current parameters into the study to reduce error and enhance accuracy by 2%. The author has raised the topic of diagnosing voltage and current imbalances in three-phase induction motors using MATLAB-based ANN methods and Arduino microcontrollers, with a 97% accuracy rate.

2. METHODOLOGY

2.1. ANN System Design

This study uses the ANN method to divide the system block diagram into three sub-systems, as shown in Figure 1:

1) The main system, which includes a power supply, current and voltage sensors, an induction motor, a microcontroller, and a mechanical load, is the primary focus of this research. This subsystem will take voltage and current data from the PZEM-004t sensor with a measurement accuracy of ±0.5% each based on the sensor specification datasheet, which will then be collected in PLX-DAQ.

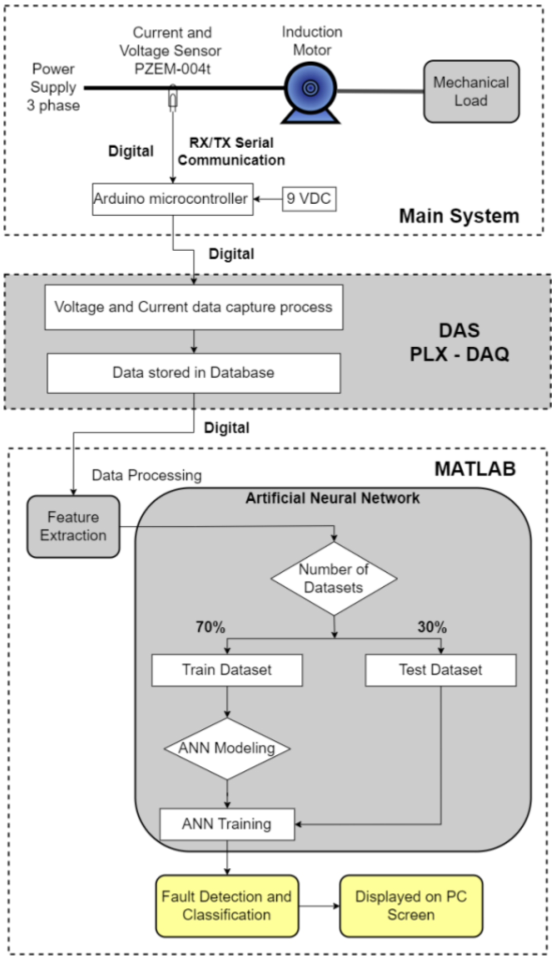


Figure 1. System block diagram.

2) The DAS PLX-DAQ data acquisition system interfaces directly with Arduino microcontrollers and sensors to gather current and voltage data from the three-phase induction motor, which then serves as a database system in MS Excel format.
3) The CPU serves as a central processing unit, utilizing MATLAB to execute the Artificial Neural Network (ANN) process from the database system. This process involves two stages: training and testing. The database provides 70% of the data for the training stage and 30% for the test stage.

The PZEM-004t sensor test revealed that each sensor has an average voltage and current error of 0.1%, as well as an RMSE of 0.0007. This is sufficient for taking measurements with minimal error. This makes the PZEM-004t sensor appropriate for use in research.

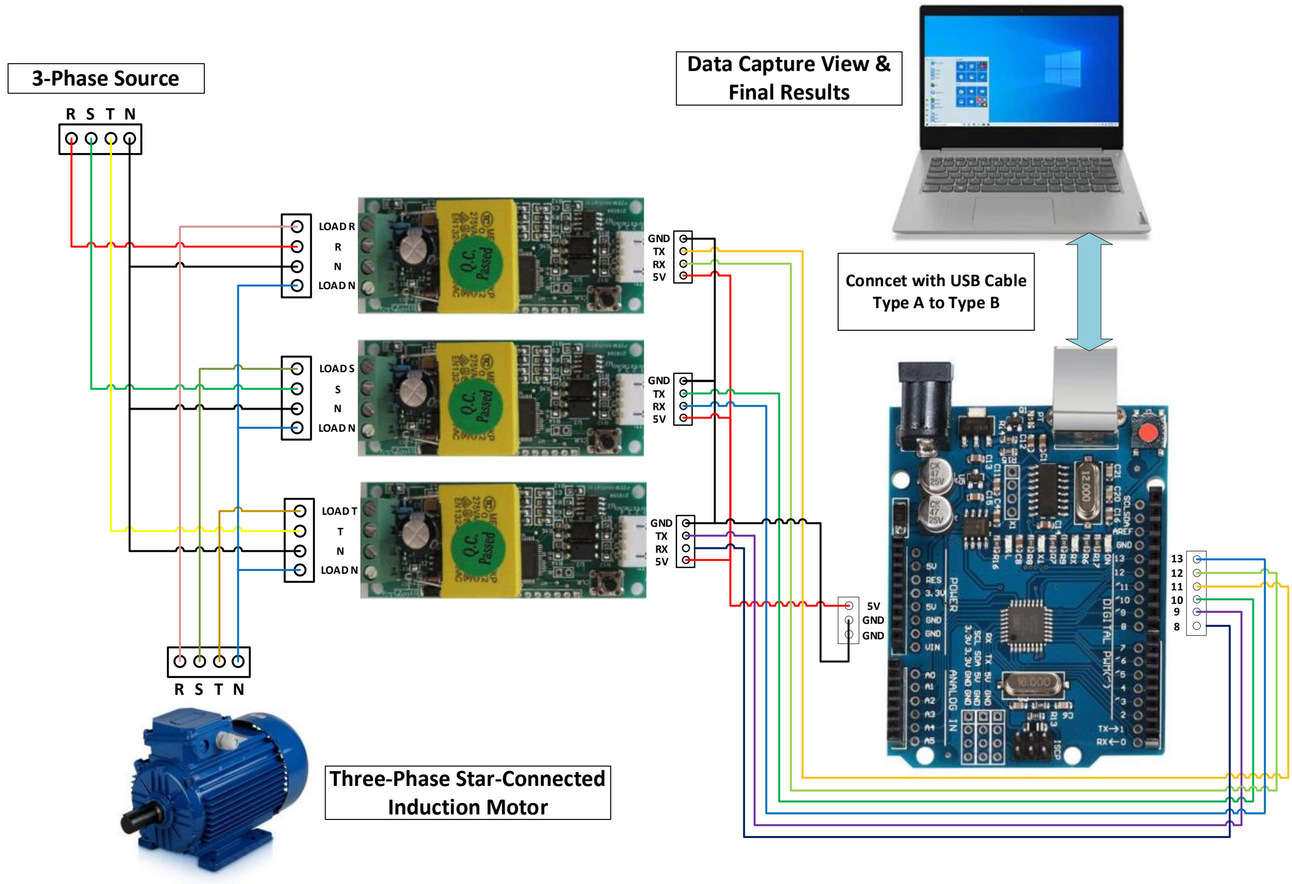


Figure 2. Data acquisition circuit.

The circuit in Figure 2, measures and reads the voltage and current of a three-phase induction motor using a single sensor for each phase. Using serial communication, the PZEM-004t sensor reads and sends data to the Arduino. The Arduino then transmits the data to the PC for display on a screen.

In determining the parameters of voltage and current imbalance, it is necessary to know in advance the standards used as a reference. The voltage unbalance standard is based on IEEE Standard 112-2004, which states that the maximum voltage imbalance value is 3% (IEEE, 2018). The American National Standards Institute, sets the maximum current unbalance value at 5% for the current imbalance standard (ANSI, 2006). We can use the following formula to find the percentage of voltage unbalance (IEEE, 2018):

$$VU = \frac{\max\left[\left|V_a - \frac{V_a+V_b+V_c}{3}\right|, \left|V_b - \frac{V_a+V_b+V_c}{3}\right|, \left|V_c - \frac{V_a+V_b+V_c}{3}\right|\right]}{\frac{V_a+V_b+V_c}{3}} \quad (1)$$

Table 1. Provides an example of a calculation for imbalance.

No	Input			Percent Unbalance	Description
	VR	VS	VT		
1.	220.8	220.9	220.5	0%	Balance
2.	220.8	220.9	225.5	1%	Balance
3.	220.8	219.9	225.5	2%	Balance
4.	220.8	217.9	228.5	3%	Balance
5.	220.8	215.9	231.5	4%	Unbalance

Table 2. Provides an example of a calculation for the current imbalance.

No	Input			Percent Unbalance	Description
	IR	IS	IT		
1.	2.92	2.90	2.94	1%	Balance
2.	2.92	2.97	2.88	2%	Balance
3.	2.94	2.82	2.77	3%	Balance
4.	2.92	2.95	2.75	4%	Balance
5.	2.90	2.75	2.62	5%	Balance
6.	2.92	2.76	2.62	6%	Unbalance

Table 3. Provides an example of achieving the ANN voltage target.

No	Input			Description	Target
	VR	VS	VT		
1.	220.8	220.9	220.5	Balance	-1
2.	220.8	220.9	225.5	Balance	-1
3.	220.8	219.9	225.5	Balance	-1
4.	220.8	217.9	228.5	Balance	-1
5.	220.8	215.9	231.5	Unbalance	1

Table 4. Provides an example of the current ANN achievement target.

No	Input			Description	Target
	IR	IS	IT		
1.	2.92	2.90	2.94	Balance	-1
2.	2.92	2.97	2.88	Balance	-1
3.	2.94	2.82	2.77	Balance	-1
4.	2.92	2.95	2.75	Balance	-1
5.	2.90	2.75	2.62	Balance	-1
6.	2.92	2.76	2.62	Unbalance	1

Where Va, Vb, and Vc represent the phase voltages. Table 1 as shown the provides an example of a calculation for imbalance. Similarly, we can use the following formula to find the percentage of current imbalance (IEEE, 2018):

$$IU = \frac{\max\left[\left|I_a-\frac{I_a+I_b+I_c}{3}\right|,\left|I_b-\frac{I_a+I_b+I_c}{3}\right|,\left|I_c-\frac{I_a+I_b+I_c}{3}\right|\right]}{\frac{I_a+I_b+I_c}{3}} \quad (2)$$

Where Ia, Ib, and Ic represent the phase currents. Table 2 as shown the provides an example of a calculation for the current imbalance.

After calculating the imbalance, labeling 1 and -1 is the next step. The aim is to simplify the ANN's comprehension of the desired outcome when presented with diverse inputs.

We provide the following conditions for labeling the voltage (see Table 3 for the result):

1) The label "-1" denotes an imbalance percentage value of 0%-3% (balance).
2) The label "1" indicates an imbalance percentage value of 4%-100%.

We specify the following conditions for labeling the flow (see Table 4 for the result):

1) A percentage value of 0%-5% (balance) indicates an imbalance.
2) The label "1" denotes an imbalance percentage value of 6%-100%.

Furthermore, the data analysis process relies on the calculation of error and accuracy. We can determine the feasibility of this research by examining the error and accuracy values from the comparison between the manual and ANN classification methods.

Mean Squared Error (MSE), provides a comparison of the actual classification and the ANN classification; a very low MSE value indicates that the ANN is well trained, and vice versa:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3}$$

where:

y_i = actual classification
$\hat{y}_i$ = predicted classification

The Root Mean Squared Error (RMSE) represents the square root of the mean squared error (MSE). Therefore, a model's prediction accuracy increases as its RMSE value decreases:

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}} \tag{4}$$

Classification Accuracy, measured in percentages. The higher the percentage of accuracy, the better the prediction result:

$$\mathrm{Accuracy} = \frac{K-IC}{K} \times 100 \tag{5}$$

where:

K = number of samples tested
IC = number of incorrect classifications

2.2. Implementation of Artificial Neural Network System

The following Figure 3 is a flow chart of the data acquisition program.

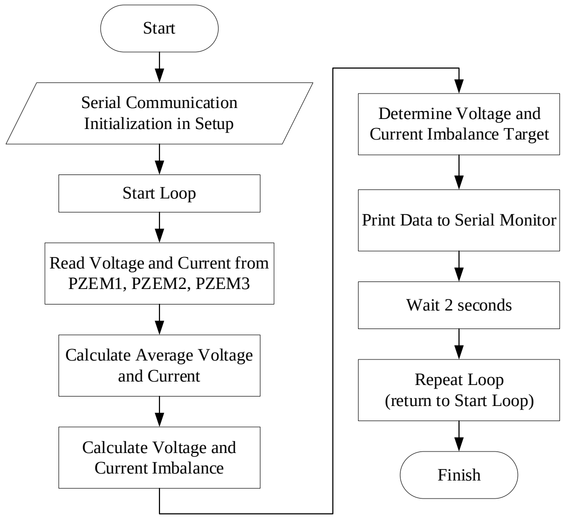


Figure 3. Flowchart of the data acquisition program.

To create an ANN classification system, you must first collect a voltage and current dataset from a three-phase induction motor with a target of -1 or 1. In the Arduino IDE software, the Data Acquisition Program for taking voltage and current datasets of three-phase induction motors uses the C/C++ language. The program uses the pre-existing PZEM-004t library on Arduino, which requires only a library call. We will compile the results of this data acquisition into a PLX-DAQ dataset. To achieve optimal ANN training outcomes, we require the following parameters as shown in Table 5.

Table 5. ANN training parameters.

Training Parameters	
Architecture	1 input, 1 hidden layer, 1 output
Training Algorithm	Feed Forward Backpropagation
Transfer Function	Tansig
Maximum Training Epoch	1000
Performance Function	Mean Square Error (MSE)
Hidden Neurons	15

Figure 4 displays the three primary layers of an artificial neural network of the ANN architecture diagram. The input layer consists of six neurons, each labeled Input 1 through Input 6, which receive the initial data for processing by the network. The hidden layer consists of 15 neurons, each labeled Hidden 1 through Hidden 15.

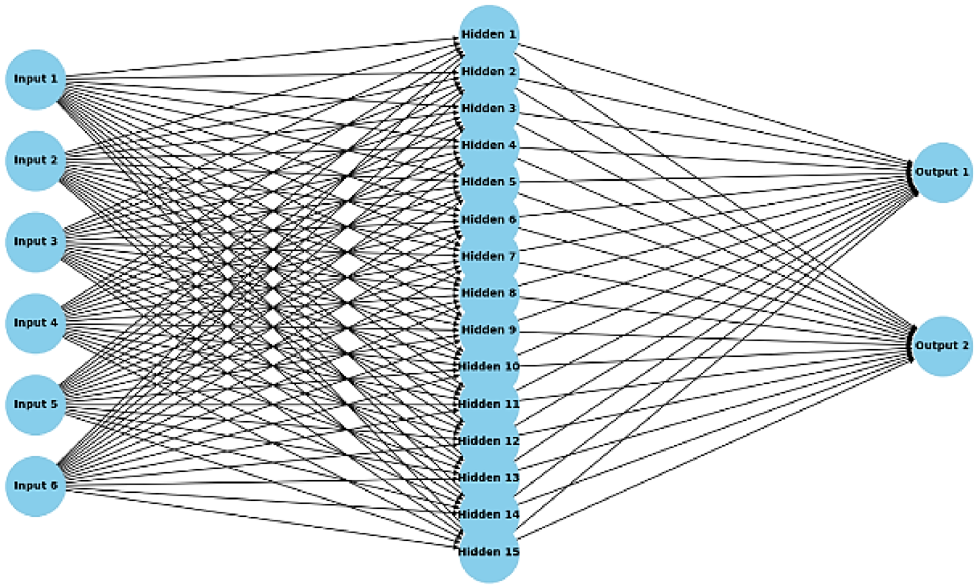


Figure 4. ANN diagram.

Each neuron in the input layer connects to every neuron in the hidden layer, forming an entire coupling between the two layers. The output layer has two neurons, designated as Output 1 and Output 2. Every neuron in the hidden layer establishes a connection with every neuron in the output layer. This network is a representation of a multi-layer perceptron (MLP) model with a single hidden layer.

Next is ANN modeling, which consists of two processes, including ANN training and testing. Both processes utilize collected datasets, with 70% designated for training and the remaining 30% for testing. We will also use the results of this modeling to call the Graphical User Interface (GUI) design process on the App Designer in MATLAB.

In this modeling process, we start by calling the ANN input dataset file, which consists of 9 columns: 1 time column, 6 input columns, and 2 target columns. We then separate 70% of the data for training and 30% for testing. Table 5 displays the ANN modeling parameters. Once we determine the parameters, we proceed with the training and testing process. We will then present the results as information to evaluate the feasibility of ANN modeling. The following Figure 5 is a flowchart of ANN modeling in MATLAB.

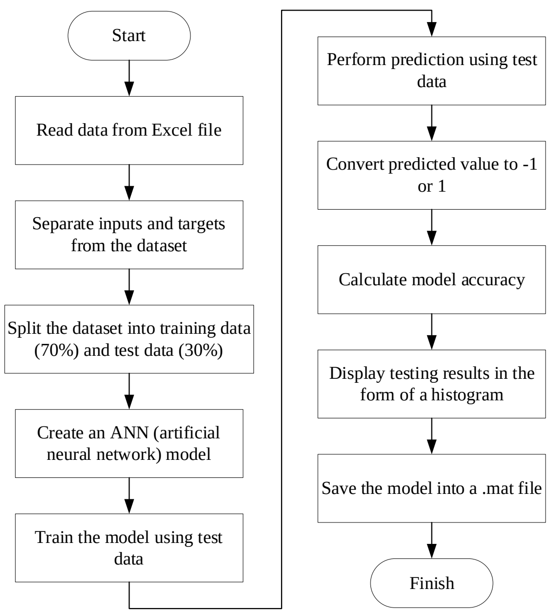


Figure 5. ANN modeling flowchart.

The following Figure 6 is a flowchart of the interface design. After modeling the ANN, design the interface in the MATLAB App Designer. The objective is to display the classification results in a graphical format. The design will include a real-time ANN system for data collection from the sensor. The ANN will then classify the data directly in real-time.

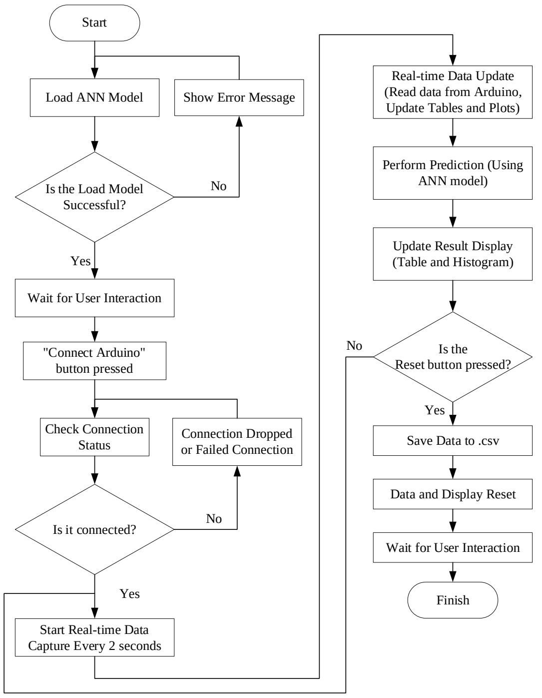


Figure 6. Flowchart of interface design.

3. RESULTS AND DISCUSSION

3.1. Realization of System Design

The following Figure 7 is a realization of the system design consisting of a three-phase induction motor, an Arduino-based three-phase power data acquisition module, and a set of Terco.

Figure 7. Realization of the system design on a three-phase induction motor.

The following Figure 8 is a picture of the realization of hardware packaging that was previously designed. White acrylic serves as the material for all components supporting this Arduino-based three-phase power data acquisition module.

Figure 8. Realization of hardware suitcase packaging.

3.2. Voltage and Current Data Collection

The data collection yielded the following results for the dataset as shown in Figure 9 and Figure 10.

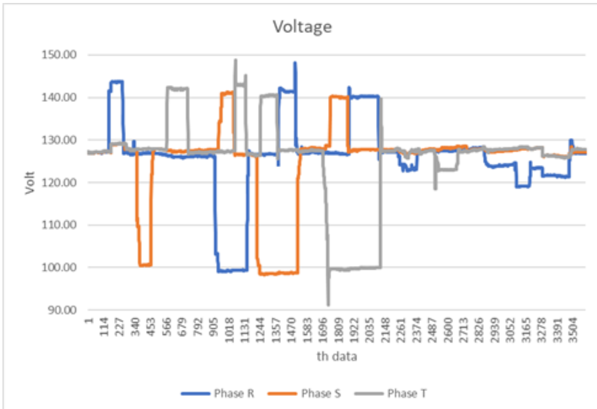


Figure 9. Voltage dataset graph.

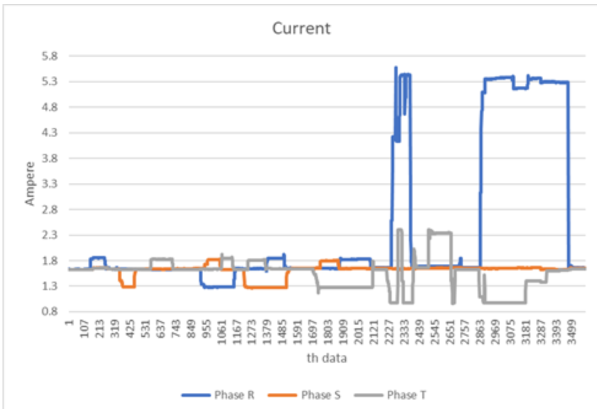


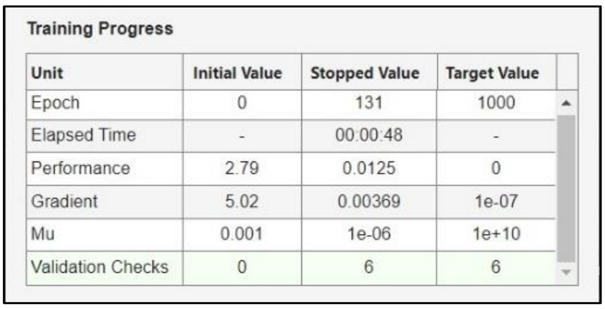
Figure 10. Flow dataset graph.

Figure 9 and Figure 10 show the results of voltage and current data collection on a three-phase induction motor with a star-connected motor that receives a 220V line-line voltage. The graph shows 3500 data points. The graph displays fluctuations in the resulting data between phases, enabling ANN to identify balanced or unbalanced voltage and current. ANN necessitates input data that fluctuates and varies with each phase, enabling it to independently determine the balanced and unbalanced state of voltage and current.

3.3. ANN Modeling Testing

The program will display important information after running the ANN modeling program, allowing users to assess the feasibility of the ANN model created. Based on Figure 11, the ANN training process took only 48 seconds, using 131 training rounds and a total of 3500 data points. The initial performance value was 2.79, and the value when stopped was 0.0125. We then stopped the gradient at 0.00369, resulting in a Mu value of 1e-06. Next, perform six validation checks corresponding to the target value. The ANN will automatically stop the training process when its performance has reached its best point, as shown in Figure 12, which shows that the ANN reached its best point at epoch 125.

Figure 13 shows that the four elements in the ANN regression modeling have reached their best target, which is close to 1. When the training element achieves a result of R = 0.99284, surpassing 0.95, we declare it feasible. Subsequently, the test element achieves a result of R = 0.95464, surpassing 0.95, thereby confirming its feasibility. Next, the validation element achieves a result of R = 0.98649, surpassing 0.95, thereby confirming its feasibility. The ALL element then receives a result of R = 0.98602, surpassing 0.95, indicating its feasibility.


Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	131	1000
Elapsed Time	-	00:00:48	-
Performance	2.79	0.0125	0
Gradient	5.02	0.00369	1e-07
Mu	0.001	1e-06	1e+10
Validation Checks	0	6	6

Figure 11. Neural network training progress.

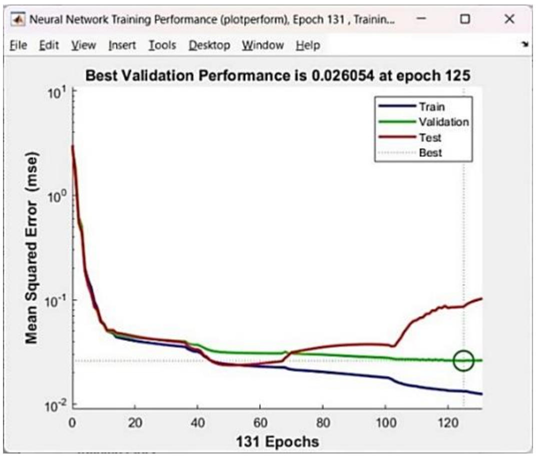


Figure 12. Performance ANN modeling.

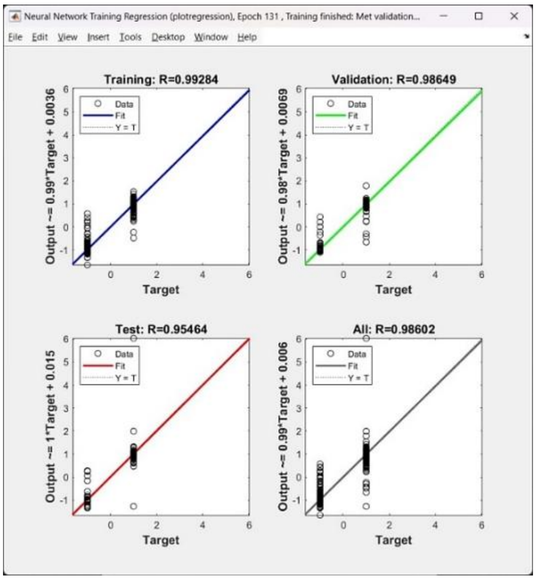


Figure 13. Regression ANN modeling.

Figure 12 and Figure 13, along with the previously provided explanation, indicate that ANN modeling is effective and suitable for use at this stage of the training process. The performance results demonstrate this, with a Best Validation Performance of 0.026054 at epoch 125 and a goal of above 0.95 for the entire regression. Based on the results, Table 6 concludes that this model is suitable for use.

Table 6. ANN modeling conclusion results.

ANN Modeling	
Total Data	3500
Accuracy Model	99.14%
Mean Squared Error (MSE)	0.023542
Root Mean-Squared Error (RMSE)	0.15343

3.4. Overall System Testing

Figure 14 displays the results of the ANN system's interface design. Above the interface are the research title and researcher name, and below them are the input and output tabs. The results of the whole system testing process are obtained from input datasets that are read in real time and displayed in the graph in Figure 15. Figure 15 voltage axes and current axes graphs demonstrate that a voltage imbalance leads to an unbalanced current between its phases, whether it spikes or decreases. For example, if there is a spike in voltage phase S at the 65th data point, there will also be a spike in current phase S. Vice versa, current imbalance affects voltage. For instance, if the 177th data point shows a decrease in current phase T, the same data shows a spike in voltage phase T, albeit not to an extreme level. Then, a CSV file stores the results of the entire system testing process, including the voltage and current inputs, as well as the ANN prediction outcomes. The aim is to preserve and store the read and predicted data in the archive.

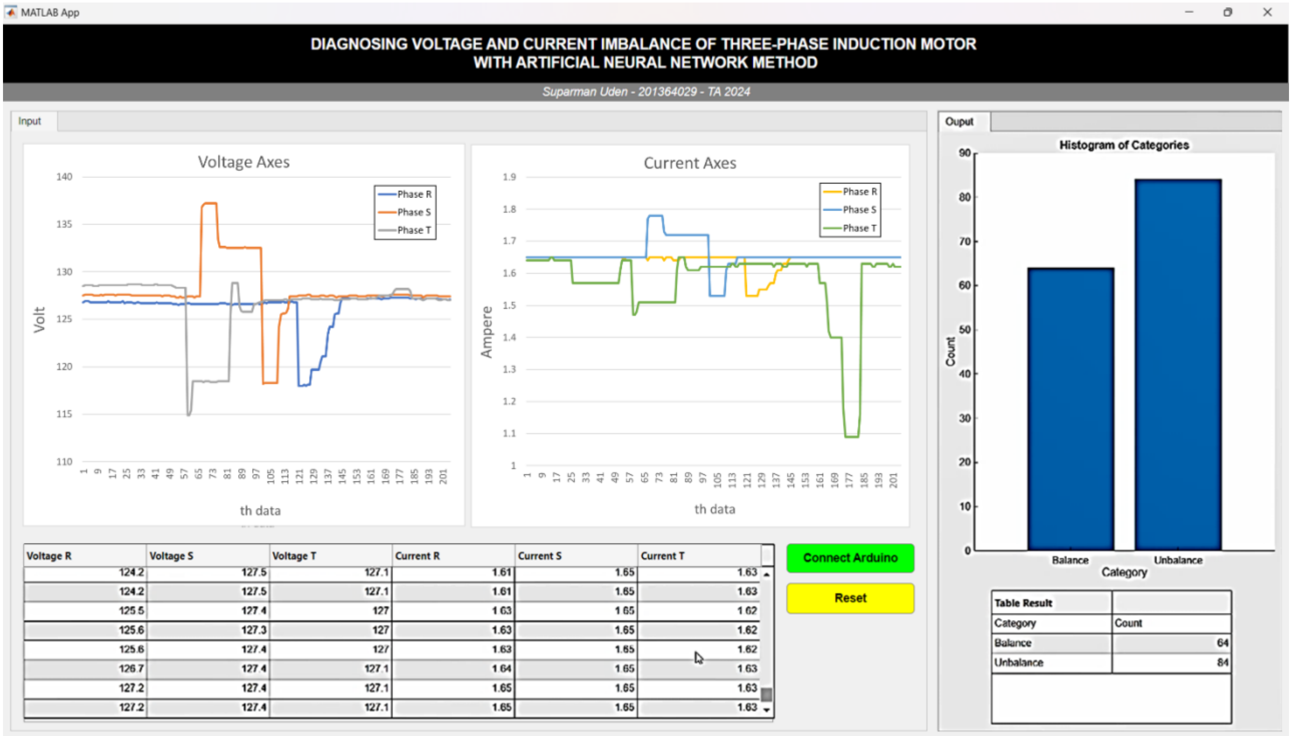
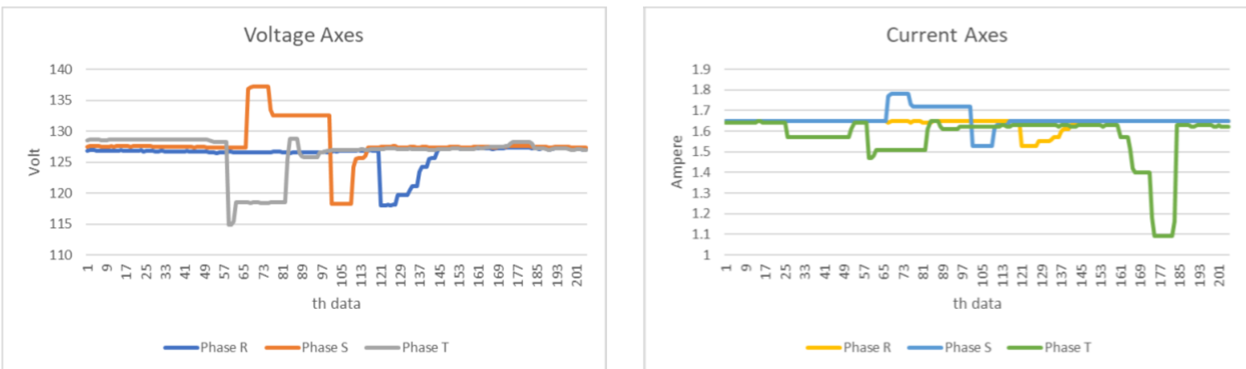


Figure 14. System interface.



(a) Voltage axes (b) Current axes

Figure 15. Voltage and current input graphs during the classification process.

Figure 16 displays the classification results of the whole system test. Testing the entire system revealed that of the 205 processed data points, 124 included balance, and 81 included unbalances.

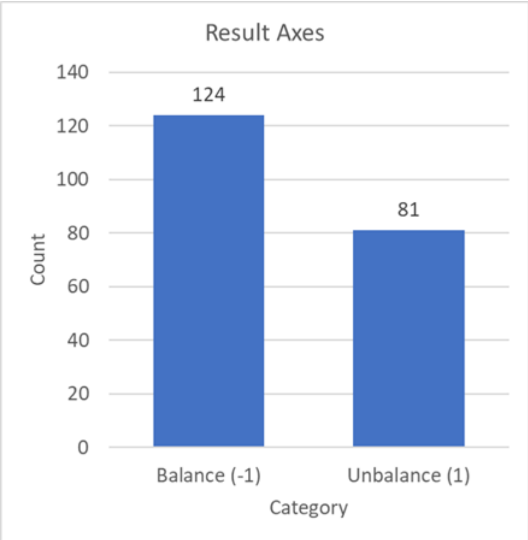


Figure 16. Realtime ANN classification results.

Table 7 shown the overall system test conclusions. The classification accuracy is 99.51%, and the error is 0.49%. The MSE value is 0.0167 and the RMSE is 0.1294, indicating a minimal error.

Table 7. Presents the overall system test conclusions.

System Testing	
Number of test voltage samples	205
Percentage Correct classification	99,51%
Percentage Incorrect classification	0,49%
Mean Squared Error (MSE)	0,0167
Root Mean-Squared Error (RMSE)	0,1294

4. CONCLUSION

A system for diagnosing voltage and current imbalances in three-phase induction motors using the Artificial Neural Network method has been successfully designed and implemented. The results of the implementation of the ANN method get an accuracy of 99.51% accuracy, seen from the results of system testing which shows that with a total of 205 realtime input data, 60.49% of data detected balance and 31.59% of data detected unbalance, with an MSE value of 0.0167 and RMSE of 0.1294. By diagnosing voltage and current imbalances in three-phase induction motors in real-time, it can help provide simple protection to determine the condition of the motor before severe damage occurs.

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